

Using Deep Learning with Spatial Transformations to Predict Protein-Ligand Binding

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## **Introduction -** Drug Discovery



- Time Consuming Expensive Labor Intensive
- Protein-Ligand Binding is Important for Drug Discovery
  - 90% of drugs on market act on proteins\*
- Protein: molecules essential for body functions
- Ligand: molecule that binds to a protein, i.e. drug



10XR - Aspirin binding

Causes anti-inflammatory effects

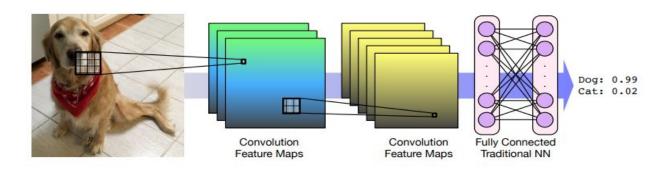
Singh RK, Ethayathulla AS, Jabeen T, Sharma S, Kaur P, Singh TP.J Drug Target. 2005 Feb; 13(2):113-9.

<sup>\*</sup>Rask-Andersen, et al., Trends in the exploitation of novel drug targets. Nature Reviews Drug Discovery, 10:579-590, Aug. 2011

### Introduction - Convolutional Neural Networks



- Deep Learning Neural networks
  - Commonly applied to analyzing visual imagery
  - Learns features of the image as "filters" or "feature maps"
  - Each additional layer allows learning at a higher level features

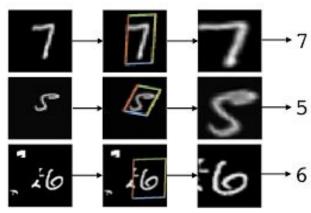


Ragoza, M. et al. Protein-Ligand Scoring with Convolutional Neural Networks. J. Chem. Information and Modeling. 942-957, April. 2017

# **Introduction - Spatial Transformer Networks**



- STNs module incorporated into CNN
- Manipulates data in multiple dimensions
- Spatially transforms data
- Resilient to perturbation
  - translation, rotation, dilation, warping

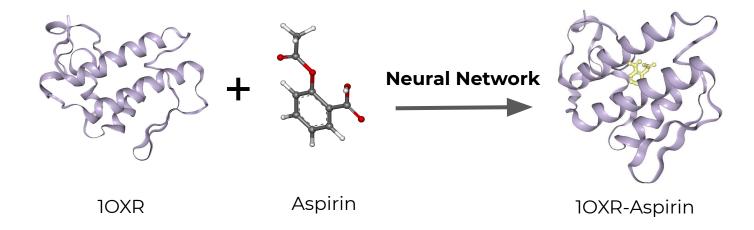


Jaderberg, M. et al. "Spatial Transformer Networks". Feb. 2016

### **Introduction -** Can we do it?



**Question:** can neural networks predict protein-ligand binding after rigid body transformations?

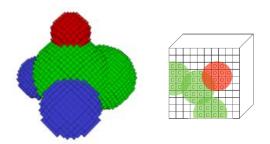


## **Method** - Ligand Voxelization and Perturbation



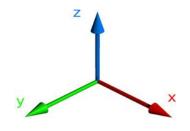
#### **3D Voxelization**

- Represents structures in cartesian coordinates
- Atoms represented as voxels



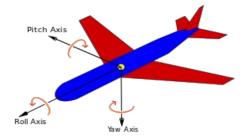
#### **Translation**

- Translated along x, y and z axis
- Error measured in angstroms



#### **Rotation**

- Translated along roll, pitch and yaw
- Error measured in radians



## **Methods - Pytorch and Caffe Outline**

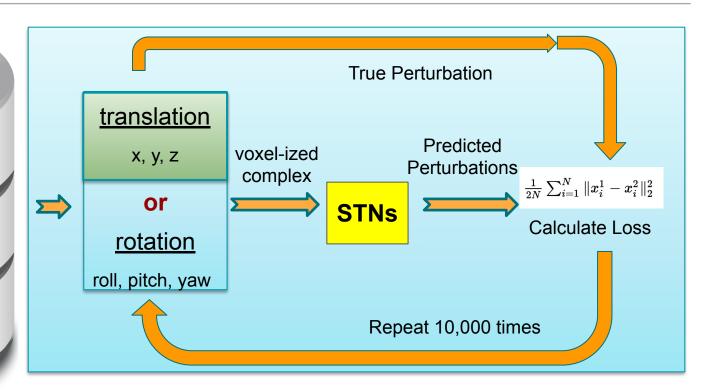




16,000 Known pairs

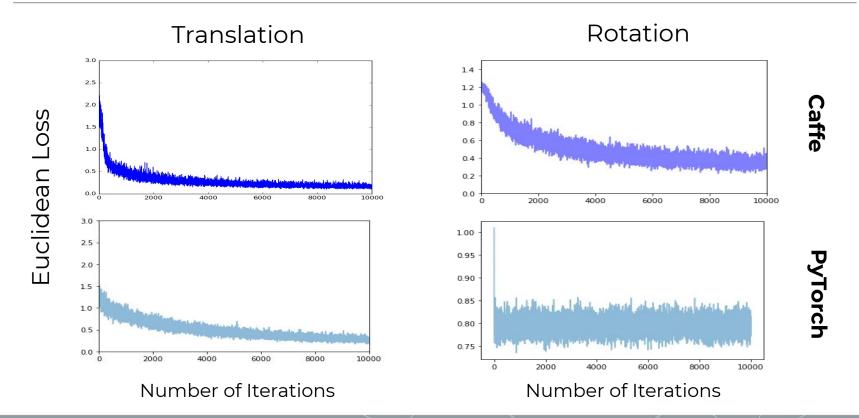
Refined set 4,463 pairs

Training set (80%)
Testing set (20%)



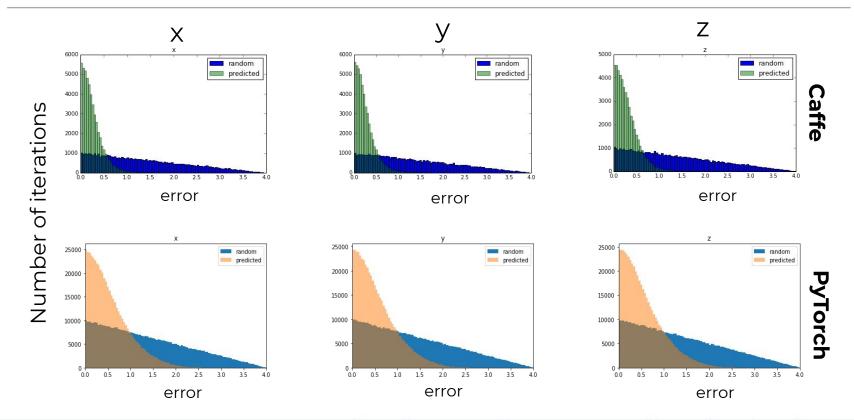
## **Results -** Loss Convergence: Caffe vs PyTorch





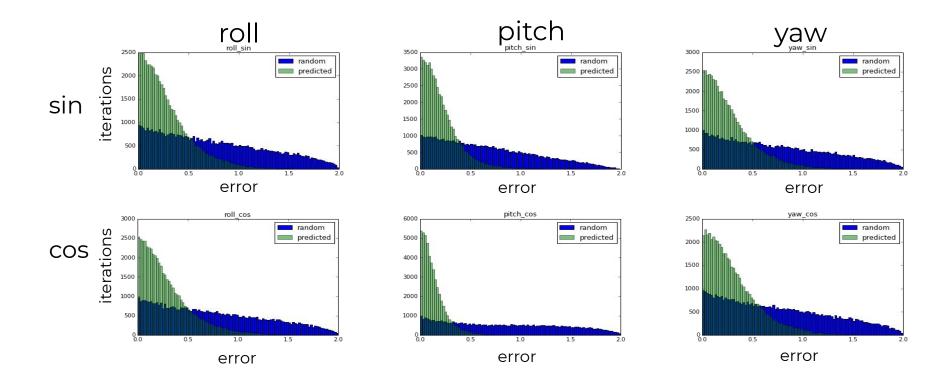
# **Results - Prediction Accuracy: Translation**





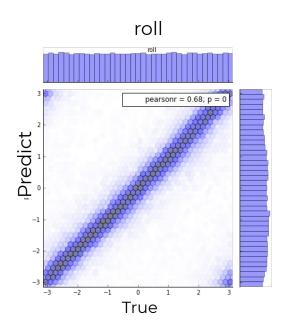
# **Results - Prediction Accuracy: Rotation-Caffe**



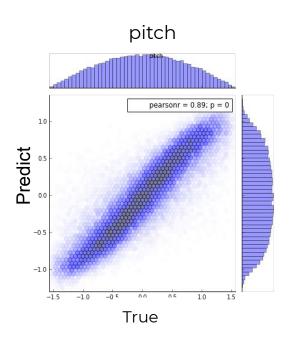


# **Results** – Correlation between predicted and true values for rotational models: Caffe

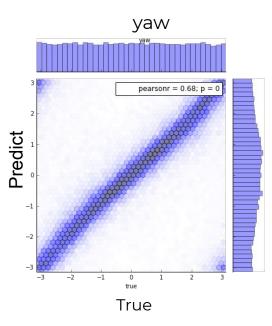




Pearson r = 0.68, p = 0



Pearson r = 0.89, p = 0



Pearson r = 0.68, p = 0

# **Results -** Summary of Pearson R



	Roll		Pitch		Yaw		Χ		Υ		Z	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
2 Angstrom Translation	-	-	-	-	-	-	0.96	0.96	0.96	0.96	0.96	0.96
Rotation	0.68*	0.68*	0.89	0.89	0.69*	0.68*	-	-	-	-	-	-
2 Angstrom Translation	-	-	-	-	-	-	0.86	0.86	0.85	0.85	0.86	0.86
Rotation	0	0	0	0	0	0	-	-	-	-	-	-

<sup>\*</sup>Indicates biased Pearson R value

#### **Conclusions**



- STNs are able to converge indicating their learning capacity.
   Caffe model seems to work better than PyTorch model
- STNs are able to learn translational perturbations using Caffe or PyTorch
- Random rotations of the ligand can be predicted by STNs but with weaker accuracy than translation using Caffe
- PyTorch model was not able to converge for rotation perturbations.
- Results are promising further testing needs to be performed

# Acknowledgements



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# Thank you!

